JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

Vol. 44, No. 4 AMERICAN WATER RESOURCES ASSOCIATION August 2008

APPLICATION OF TABU SEARCH ALGORITHM WITH A COUPLED ANNAGNPS-CCHE1D MODEL TO OPTIMIZE AGRICULTURAL LAND USE[1]

Honghai Qi, Mustafa S. Altinakar, Dalmo A.N. Vieira, and Bahram Alidaee[2]

ABSTRACT: A principal contributor to soil erosion and nonpoint source pollution, agricultural activities have a major influence on the environmental quality of a watershed. Impact of agricultural activities on the quality of water resources can be minimized by implementing suitable agriculture land-use types. Currently, land uses are designed (location, type, and operational schedule) based on field study results, and do not involve a science-based approach to ensure their efficiency under particular regional, climatic, geological, and economical conditions. At present, there is a real need for new methodologies that can optimize the selection, design, and operation of agricultural land uses at the watershed scale by taking into account environmental, technical, and economical considerations, based on realistic simulations of watershed response. In this respect, the present study proposes a new approach, which integrates computational modeling of watershed processes, fluvial processes in the drainage network, and modern heuristic optimization techniques to design cost effective land-use plans. The watershed model AnnAGNPS and the channel network model CCHE1D are linked together to simulate the sediment and pollutant transport processes. Based on the computational results, a multi-objective function is set up to minimize soil losses, nutrient yields, and total associated costs, while the production profits from agriculture are maximized. The selected iterative optimization algorithm uses adaptive Tabu Search heuristic to flip (switching from one alternative to another) land-change variables. USDA's Goodwin Creek experimental watershed, located in Northern Mississippi, is used to demonstrate the capabilities of the proposed approach. The results show that the optimized land-use design with BMPs using an integrated approach at the watershed level can provide efficient and cost-effective conservation of the environmental quality by taking into account both productivity and profitability.

(KEY TERMS: land-use planning; watershed management; simulation; optimization; economic benefits; AnnAGNPS; Tabu search; nonpoint source pollution; Goodwin creek.)

Qi, Honghai, Mustafa S. Altinakar, Dalmo A.N. Vieira, and Bahram Alidaee, 2008. Application of Tabu Search Algorithm With a Coupled AnnAGNPS-CCHE1D Model to Optimize Agricultural Land Use. *Journal of the American Water Resources Association* (JAWRA) 44(4):866-878. DOI: 10.1111/j.1752-1688.2008.00209.x

[1]Paper No. J06161 of the *Journal of the American Water Resources Association* (JAWRA). Received November 10, 2006; accepted February 25, 2008. **Discussions are open until February 1, 2009**.

[2]Respectively, Project Engineer, NMP Engineering Consultants, Inc., ICC Project Management Office, 11710 Beltsville Drive, Beltsville, Maryland 20705; Associate Director and Research Professor, National Center for Computational Hydroscience and Engineering (NCCHE), The University of Mississippi, Carrier Hall Room 102, University, Mississippi 38677-1848; Research Hydraulic Engineer, USDA – ARS – National Sedimentation Laboratory, Watershed Physical Processes Research Unit, 598 McElroy Drive, Oxford, Mississippi 38655-1157; and Professor, Department of Management Information System and Production Operations Management, School of Business Administration, University of Mississippi, Mississippi 38677 (E-Mail/Qi: HQi@nmpengineering.com)

INTRODUCTION

In recent decades, there has been a growing consensus that an integrated planning and management effort at the watershed scale is needed for achieving long-term sustainability of agriculture and rural communities (Fulcher, 1996). This has led to a renewed interest in Integrated Watershed Management (IWM), which was first introduced by the National Water Commission in the United States (U.S.) in 1968 (Bulkley, 1995). IWM can be defined as "A method to encompass and coordinate all of a watershed's potential uses, services, and values in management decisions and regulatory activities rather than attempting to maximize selected resources or regulate individual pollutants" (Ballweber, 1995).

One of the most important components of the IWM is the agricultural land-use planning. Land-use planning not only plays an important role in the social and economic development of the watershed, but also directly influences various environmental processes such as soil erosion in upland areas, sediment and nutrient loadings into streams, water quality and stream morphodynamics. It is well recognized that the land-use planning has a major impact on the morphodynamics and water quality of the streams. One of the major contributors to degradation of surface and ground-water quality, the agricultural nonpoint source (NPS) pollution, in the form of sediment, nutrients and pesticides contributed by farmlands, is also determined by land-use planning and management practices (Srivastava *et al.*, 2002).

To mitigate NPS pollution, the U.S. Congress amended the federal Clean Water Act (CWA) in 1972, 1977, and 1984. As part of these governmental regulations, implementation of best management practices (BMPs) emerged as one of the effective methods to control NPS pollution (Veith *et al.*, 2003; Zhen *et al.*, 2004). These BMPs range from structural measures, such as contours, terraces, stormwater detention basins, to nonstructural practices, e.g., conservation tillage, crop rotation, and integrated management of pesticides.

Despite these developments, the current practice does not yet include a widely accepted methodology to include the water quality component (Wang, 2001) in land-use planning. The NPS management strategy uses a three-step procedure: critical area identification, BMP selection, and area-wide comprehensive planning. Currently, the suitability or effectiveness of a BMP is determined by monitoring or modeling (for example with AnnAGNPS or SWAT) pollutant levels before and after BMP implementation (Gilliam, 1994; Lin *et al.*, 2002). However, implementing a large number of locally designed BMPs without proper consideration of the entire watershed response may not be cost effective and may lead to redundancies. It is also difficult to comply with regulations in place or meet legal and cost sharing requirements when BMPs are designed based on local considerations.

Effective watershed management requires an understanding of basic hydrologic and biophysical processes in the watershed. A number of simulation models at the watershed scale have been developed to evaluate water quality parameters affected by agricultural practices. In streams, engineers use hydrodynamic models to evaluate sediment aggradation/degradation, pollutant transport. In addition, recent advances in mathematical optimization techniques opened up new paths to explore for selecting optimal scenarios in water resources management. When faced with several alternative management options, these techniques can significantly enhance the quality of the decision-making process. A newly developed solution approach, which efficiently interfaces a watershed model with an optimization technique, usually provides better results than using them individually. Some system-based research involving selection of the most suitable design from a pool of scenarios at the watershed scale has been conducted to guarantee the cost-benefit effectiveness of the solutions over a long time period (Srivastava *et al.*, 2002; Harrell and Ranji, 2003; Veith *et al.*, 2003; Cerucci and Conrad, 2003,; Zhen *et al.*, 2004). Among these researches, Genetic Algorithm (GA) was chosen as the primary optimization technique, as it provided better BMP placement scenarios with regard to reducing NPS loadings and cost than randomly assignment of BMPs. However, from the modeling concepts and practical application point of view, GA has the following drawbacks and shortcomings:

1. GA requires defining a representation of the optimization problem, i.e., a genome in GA's terminology. Success of the GA is dependent on an appropriate problem representation. For the land-use planning and BMP placement problem, this process involves creating representations of cropping and management practices for every field in the watershed. For example, Srivastava *et al.* (2002) used a two dimensional binary string to represent 15 different cropping and management practices on a 45-cropland watershed. The total bits of these two dimensional strings amount up to $45 \times 4 = 180$. As the alternative cropping and management practices and the field number increases, the definition process becomes complicated and takes lot of computer time and memory to store those representations. Also, this process is highly problem-specific and cannot be readily applied to other problems.

2. For GA to work, a genetic operator which involves three primary components – initialization, mutation, and crossover – must be defined. A number of parameters for those components, like the mutation rate, replacement probability, and solution fitness, should be fine-tuned so as to get satisfactory results. For a large size problem, this process can be extremely difficult and very time consuming.
3. GA requires multiple start solutions and the number of these randomly generated solutions should be equal to, or even greater than the dimension of the problem. To represent the most general cases and reflect the characteristics of the search space, the multiple starting solutions should be designed diversely and distributed uniformly in the solution spaces. Previous researchers suggested using hypothetical randomly generated land-use scenarios as multiple initial solutions, but it turned out later that this may not yield good optimization results as the dimension of the problems increased.
4. The selection process of GA emphasizes on randomness rather than responsive explorations. As Zhen *et al.* (2004) pointed out, GA is based on a probabilistic heuristic search approach rather than deterministic search rules. Sometimes this randomness can lead to a near optimal solution, but other times the convergence rate maybe very low and even divergent.

The alternative approach proposed in this study integrates computational modeling and modern heuristic optimization techniques, and offers a new method of effective land-use planning with BMP design at the watershed scale. This approach uses an integrated watershed and channel network model to simulate sediment and pollutant transport processes. The calculated results are then used to set up a multi-objective function to simultaneously minimize soil losses, nutrient yields and the implementation/maintenance costs, and to maximize the production profits from agriculture. The solution procedure involves the use of Tabu Search (TS) heuristic to flip land-use change variables. The use of a set of binary variables is a new and novel approach of formulating such a complicated problem, and the TS heuristics overcome some of the difficulties encountered when applying GA in land-use planning and BMP placement problems. The proposed approach is designed in modular fashion, which allows for easy component adjustment and modification while maintaining the basic conceptual framework. Application to a case study in USDA's Goodwin Creek watershed located in Northern Mississippi demonstrates that the optimized land-use plan using an integrated approach can provide cost-effective conservation of the environmental quality.

WATERSHED MODEL – ANNAGNPS

AnnAGNPS is a watershed simulation tool developed jointly by USDA-ARS and NRCS to aid in the evaluation of long term, hydrologic and water quality responses to agricultural management practices (Cronshey and Theurer, 1998). The model analyzes a watershed subdivided into suitably small cells of homogeneous land use, land management, and soil types. These cells are all hydrologically connected by a dendritic river network leading to a single watershed outlet.

AnnAGNPS is a batch process, distributed parameter, continuous simulation model with daily time step. It uses Revised Universal Soil Loss Equation (RUSLE) to simulate surface runoff and erosion, and also determines the pollutant loadings from land surfaces. Runoff quantities are calculated based on runoff curve numbers. In general, the pollutant loadings exist in two phases: dissolved (solution) in the surface runoff and attached (adsorbed) to clay size particles resulting from sheet and rill and from gully erosion carried into the stream system by the surface runoff. AnnAGNPS can also assist in determining BMPs, total maximum daily load (TMDLs), and can be used for risk, cost, and benefit analysis.

CHANNEL NETWORK MODEL – CCHE1D

CCHE1D is a general purpose one-dimensional channel network model developed by National Center for Computational Hydroscience and Engineering (NCCHE) at the University of Mississippi. It is coupled with AnnAGNPS to simulate flows and sedimentation processes in dendritic channel networks. The CCHE1D model can simulate unsteady and nonequilibrium fractional sediment transport, bed aggradation and degradation, bed material composition, bank erosion, and the resulting channel morphologic changes, and it overrides the simpler channel routing module of AnnAGNPS.

The water quality module (Vieira, 2004) can compute transport and fate of general pollutants, nutrient dynamics, and water temperature based on the loadings obtained from AnnAGNPS by means of a results file. CCHE1D model has been extensively verified and validated. Wang *et al.* (2002) presented some applications of the model. The reaction kinetics of nitrogen and phosphorus in CCHE1D can be modeled in two ways. One is using multiple state varibles, like particular organic nitrogen/phosphorus, dissolved organic nitrogen/phosphorus, ammonia nitrogen, nitrate nitrogen, and total inorganic phosphorus. The other one is modeling them as single state varibles, namely, total organic nitrogen and total organic phosphorus. The second approach was chosen because these varibales are sensitive to land-use changes than the single varibales in the current case studies.

A FRAMEWORK FOR OPTIMIZATION OF LAND-USE PLANS

The optimal land-use design at watershed scale requires minimizing or maximizing several objective functions simultaneously under a set of defined constraints, which may involve equality, inequality, and variable bounds. Mathematically, this can be described as a vector optimization

$$\underset{x \in C}{\mathrm{Max}} \text{ or Min } F(x) = [f_1(x), f_2(x), \ldots, f_n(x)]$$
$$\text{with } n \geq 2, C = \{x : g(x) \leq 0 \text{ or } > 0, \ a \leq x \leq b\} \quad (1)$$

It is highly unlikely that a given combination of design parameters can maximize (or minimize) all the objective functions, $f_1(x), f_2(x), \ldots, f_n(x)$, at the same time. Therefore, a tradeoff between the objectives becomes necessary. Various methods have been proposed to solve such vector optimization problems. One of the commonly used methods is to combine these multiple objective functions into a single optimization function, $F(x)$. This operation is not trivial, and can be quite challenging when the individual objective functions have different units and magnitudes (Veith *et al.*, 2003). This difficulty can be overcome by nondimensionalizing objective functions, and by rescaling their magnitude to fit within a common range.

The present research focuses on the land-use planning in agricultural watersheds, for which two objective functions are defined: environmental score and economical score. The first objective function, f_p, called *environmental score*, evaluates the sediment and pollutant concentration levels in the streams, which depend on the yields (water, sediment, pollutants, and nutrients) coming from the agricultural fields. The yields and the concentration levels should be calculated using appropriate simulation models. The second objective function, f_e, called *economical score*, evaluates the net economical benefit based on the implementation and

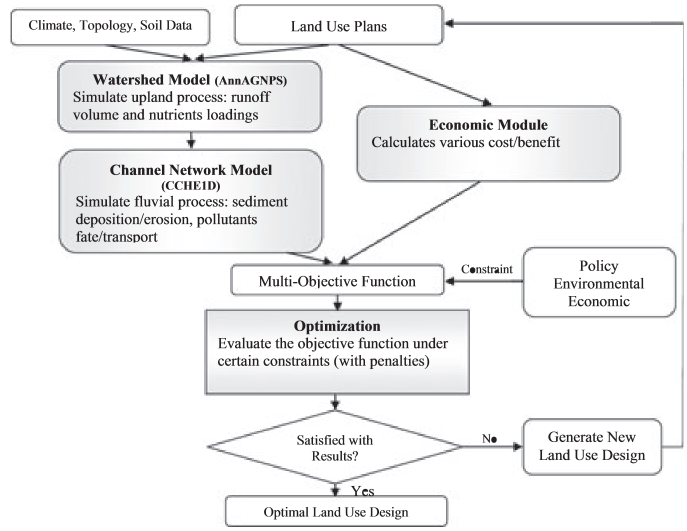

FIGURE 1. Multi-Objective Optimization Framework of Land-Use Planning.

operational costs of land, and the production benefits from agricultural activities. These are calculated based on the land-use plan, the BMP implementation scenario, and the available economic data.

The proposed multi-objective decision making (MODM) framework for optimal agricultural land-use planning is depicted in Figure 1. First, the integrated modeling system including a watershed model, a channel network model, and an economic model is launched with the current land-use configurations. Computational results of sediment yield and pollutant levels from channel network model at key locations are recorded, as well as the total cost/benefit from such land-use scenario. The decision maker then formulate their objective functions from those computed results, along with various constraints concerning physical, social, and environmental issues, also with land owner's preferences into a multi-objective optimization problem. The stakeholder can also attach their weighting factors to assign relative importance among objectives. By using a solution technique involving the use of metaheuristic optimization methods, land-use changes will be made and new land-use scenario will be generated and simulated. This process follows an iterative manner until the satisfactory land-use plans are obtained.

MULTI-OBJECTIVE FUNCTION AND CONSTRAINTS

The computational results from CCHE1D model, i.e., the sediment, pollutant, and nutrient values are used to define the environmental score. Generally there are multiple pollutants of interest that we would like to control, a unique pollutant-targeting criterion can be set for each pollutant and the individual environmental scores weighted against each other in terms of importance. The weighting factors should be fractions adding up to 1. The weighted individual environmental scores p_i are combined by the following equation to create a single total pollutant score f_p.

$$f_p = \frac{\sum_{i=1}^{N_i} \beta_i p_i}{\sum_{i=1}^{N_i} \beta_i}, \tag{2}$$

where i is index of pollutant considered, $1 < i < N_i$ and N_i is total number of pollutant, p_i is environmental score of individual pollutant i, the weighting factors β_i is the relative importance of each pollutant in the overall environmental score. Note that $\sum_{i=1}^{N_i} \beta_i = 1$.

In the watershed, several key locations k = 1, 2,…K can be selected. For each site, a weighting factor $\omega_{i,k}$ can be defined for each pollutant i. Note that $\sum_{k=1}^{N_k} \omega_{i,k} = 1$.

The environmental score for a single pollutant, p_i, is calculated from Equation (3)

$$p_i = \sum_{k=1}^{N_k} \left(\omega_{i,k} \frac{\sum_{t=1}^{N_k} p_{i,k,t}}{\sum_{t=1}^{N_k} p^*_{i,k,t}} \right), \tag{3}$$

where t is index of simulation time step, $1 < t < N_t$ and N_t is total number of time steps, $p_{i,k,t}$ is loadings of pollutant i at site k at time t, $p^*_{i,k,t}$ is baseline scenario loadings of pollutant i at site k at time t. For some land-use scenarios with BMPs, the pollutant is reduced from the baseline scenario, that is, p_i changes from 1 to 0. Otherwise, p_i may be greater than 1.

The economic module is used to evaluate both agricultural production cost/benefits and the BMPs implementation/maintenance costs (i.e., the net benefits). It is calculated from the baseline scenario, which is the current land use and management configuration of the watershed

$$f_b = \sum_{l=1}^{N_L} A_l B_m Y_m - \sum_{l=1}^{N_L} A_l (OC_m), \tag{4}$$

where f_b is the base line economic return for the current land-use scenario in the watershed; l is land unit identification index in the watershed, l = 1, 2, 3,…N_l and N_l is the total number of land units; m, is current land-use option index, m = 1, 2, 3,…M; A_l is area of field l in ha; Y_m and B_m are the actual crop yield and production returns for land-use type m, in bu/ha and \$/bu, respectively; and OC_m is the total operational cost for land-use type m (which contains direct cost, fixed cost, irrigation cost, BMP cost etc.), in dollars.

The economic score, f_e, after land use and BMP changes for the watershed is calculated a set of binary variables, using the following equation:

$$f_e = f_b + \sum_{l=1}^{N_l} y_{l,m,n} A_l [(B_n Y_n - B_m Y_m) - (OC_n - OC_m)]. \tag{5}$$

n is the future land use option index, n = 1, 2, 3, …, N; where $y_{l,m,n}$ is binary variable indicating whether land-use changes from type m to type n in land l, $y_{l,m,n}$ in; {0, 1} and $m \neq n$, in the above equation, only nonzero $y_{l,m,n}$ are considered. Note that

$$\sum_{\substack{n=1 \\ n \neq m}}^{M} y_{l,m,n} \leq 1, \quad l = 1, 2, \ldots, N_l, \tag{6}$$

which states that any land can have at most one land-use change from type m to n (i.e., $y_{l,m,n}$ = 1, or no land-use change, $y_{l,m,n}$ = 0) (Qi *et al.*, 2005).

The multi-objective function, F, is constructed by combining the environmental and economical scores in the following Equation (7). It was designed to maximize the pollutant reduction rate, while at the same time there were slight penalty associated with the decrease in net return. The use of the exponential term has been proved to produce better results than simple additive method of adding individual objective functions (Srivastava *et al.*, 2002)

$$\text{Max } F = (1 - f_p) \exp[s_e (f_e - f_b)], \tag{7}$$

where s_e is a constant that scales the strength of the cost constraint. For the present study, a value of $s_e = 5 \times 10^{-4}$ is found to be most suitable. For other applications, this constant value should be defined to scale the objective function values adequately. Note that the exponential term $\exp[s_e (f_e - f_b)]$ in the equation becomes slightly greater than 1 when ($f_e - f_b$) is positive (net economic gain, favoring such land-use plans), and less than 1 when ($f_e - f_b$) is negative (net economic loss, rejecting such land-use plans).

The multi-objective function is subject to two types of constraints, policy constraints and water quality regulations. One example of a typical policy constraint, as indicated by Equation (8), requires that the total area for the land-use type m should be equal or less than a target value, T_m, defined in hectares for the entire watershed

$$\sum_{l=1}^{N_l} A_l\Big(1-\sum_{\substack{n=1\\ n\neq m}}^{M} y_{l,m,n}\Big) \le T_m \quad m=1,2,\ldots,M \tag{8}$$

Other types of policy constraints may include the following: the water quality regulations require that the average annual pollutant loads at key sites should be less than a maximum allowed value for that site, as in Equation (9)

$$L_{i,k} \le L_{i,k}^{\max} \quad i=1,2,\cdots,N_i\;; \quad k=1,2,\cdots,N_k \tag{9}$$

where $L_{i,k}$ and $L_{i,k}^{\max}$ are the average and maximum allowed annual loads for pollutant i at key site k. Similar constraints may also be defined at any given time to satisfy TMDL requirement.

In reality, not all the farmers will accept all land-use types and BMPs, rather, they may have preferences for certain types over others. Their preferences can be obtained by interviewing them and getting their views (Gitau, 2003). To achieve a participatory decision making framework, land owners' preference are also taken into account as constraints. Land owner can rank possible land-use types in the order of his/her preference

$$\begin{aligned} R_{o,n} \le R_{o,m}, \quad & o=1,2,\ldots,O,\\ & m,n=1,2,\ldots,M \text{ and } m\neq n, \end{aligned} \tag{10}$$

where o is land owner index; o = 1, 2,…,O; $R_{o,m}$, $R_{o,n}$ are ranks assigned to land-use option m, n by the land owner o. (The lower the number, the higher the rank.)

CONSTRAINTS HANDLING USING MULTIPLICATIVE PENALTY METHOD

The general constrained optimization problem has the following form as in Equations (11) and (12)

$$\text{Max } F \tag{11}$$

Subject to

$$g_j \le b_j \text{ and/or } g_j \ge b_j, \tag{12}$$

where F is the objective function, g_j is the jth constraint, and b_j is the constant constraint upper/lower bound.

Generally, the optimization approach reformulates the constrained problem into unconstrained one by incorporating constraints into objective function. In the traditional approach, which is referred to as the Additive Penalty Method, a penalty cost that is proportional to the total violation on each of the constraints may be added to the objective function. A newly developed approach, called Multiplicative Penalty Method (Hilton and Culver, 2000), multiplies the objective function with a factor proportional to the total amount of violation. In this research, the objective function multiplier that penalizes an infeasible solution, pen, is given by the linear function (13)

$$\text{pen} = 1.0 + \sum_{j=1}^{J} \delta_j v_j, \tag{13}$$

where δ_j is the penalty weight for violating constraint v_j ($v_j > 0$). The constraint violation is measured by

$$v_j = \max\left(0, \frac{g_m - b_m}{g_m}\right), \tag{14}$$

for $g_j \le b_j$ (less than or equal to) type constraints, and

$$v_j = \left|\min\left(0, \frac{g_m - b_m}{b_m}\right)\right| \tag{15}$$

for $g_j \ge b_j$ (greater than or equal to) type constraints.

When a solution satisfies constraints, v_j is equal to 0; otherwise, v_j is greater than 0 and increases as the magnitude of violation increases. Note that v_j takes the range between (0, 1). For example, Equation (8) can be transformed to the following form:

$$v_{j,m} = \max\left(0, \frac{\left(\sum_{l=1}^{N_l} A_l\right) - T_m}{\sum_{l=1}^{N_l} A_l}\right), m=1,2,\ldots,M \tag{16}$$

The multi-objective function is now taking the following form:

$$\text{Max pen}^{-\exp\left[\text{kn}(\text{IN}/\text{IN}_{\max})\right]} \cdot F, \tag{17}$$

where IN is the iteration number, $\text{IN}_{\max}$ is the maximum iteration number, and kn is a tuning parameter. If a solution results in no violations in all the constraints, then $\text{pen}^{-\exp\left[\text{kn}(\text{IN}/\text{IN}_{\max})\right]}$ is 1, and the objective function value is equal to the original objective function value. If some of the constraints are violated, then $\text{pen}^{-\exp[\text{kn}(\text{IN}/\text{IN}_{\max})]}$ is less than 1. The objective function value will decrease, as a less-than-one penalty factor is multiplied to the original objective function value.

SOLUTION PROCEDURE USING TS HEURISTIC

The philosophy of TS is to derive and exploit a collection of principles of intelligent problem solving

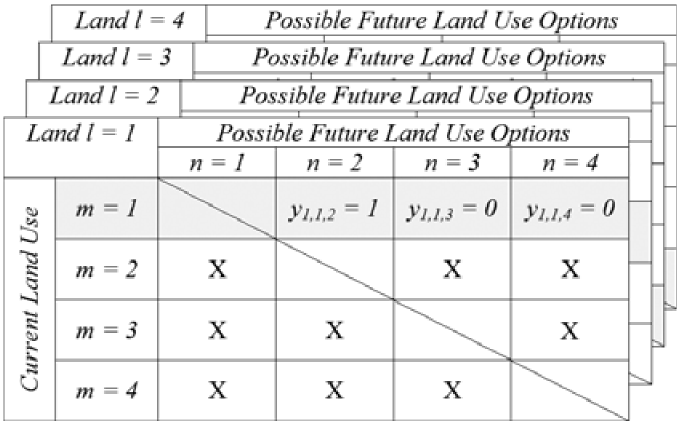

FIGURE 2. Binary Variables for Land-Use Change.

(Glover and Laguna, 1997). As a memory-based heuristic, TS draws from artificial intelligence concepts (Glover *et al.*, 1993; Swisher *et al.*, 2000). Starting with a single scenario, the basic form of the heuristic uses gradient or neighborhood search techniques to evaluate and compare scenarios. The process narrows the search space by maintaining a dynamic Tabu list of recent successful move scenarios. The Tabu list helps prevent moves in nonimproving directions so that successive scenarios become increasingly optimal.

To use TS algorithm, the land-use optimization problem is first modeled with set of binary (0-1) variables. TS guides a local heuristic search procedure to explore the solution space. Here the local search procedure refers to search that uses an operation called "*move*" to define the neighborhood of any given solution. For example, in the current optimized land-use planning problem, this move can be defined as flipping the land change binary variable $y_{l,m,n}$ from 0 to 1 (or flip it back from 1 to 0), which indicates that land-use change from type m to type n is taken place in land parcel l (Figure 2).

As shown in Figure 2, if land l has current type m = 1 and there are three future land-use options (n = 2, 3, and 4), then there would be three binary land change variables, namely, $y_{1,1,2}$, $y_{1,1,3}$, and $y_{1,1,4}$ defined for land l = 1. If the future land-use is chosen to be type n = 2, then $y_{1,1,2}$ is set to 1, while $y_{1,1,3}$ and $y_{1,1,4}$ all remain 0. All land-use change variables for other lands are defined in the similar way. Table 1 illustrates this multi-flip TS algorithm designed to search for the optimized land-use design.

However, in creating an efficient TS heuristic for a particular problem type, the structure of the Tabu list must be designed carefully to prevent premature elimination of potential solutions (Veith *et al.*, 2003). Ideally, the memory process used by the search should not only remember recent moves (short-term memory) but also have some way of looking back into longer-term memory and determining which patterns are working and which are not. In the present approach, a set of good solutions found so far are all stored. When iterations reach a level where the overall objective function can no longer be improved, the search algorithm looks for a previous solution farthest from the currently visited region. This solution serves as the initial solution for starting a new search in regions that have not yet been visited. The distance between solutions is calculated using the Hamming distance (Vandeginste *et al.*, 1998). The Hamming distance between two solution sets r_1 and r_2 is given by

$$
\begin{aligned}
&d(r_1,r_2)=\sum_{l=1}^{N_l}\sum_{n=1}^{N}\delta(r_1,r_2)_{l,m,n},\\
&\text{where } \delta(r_1,r_2)_{l,m,n}=1, y(r_1)_{l,m,n}\neq y(r_2)_{l,m,n},\\
&\qquad\quad \delta(r_1,r_2)_{l,m,n}=0, y(r_1)_{l,m,n}=y(r_2)_{l,m,n}
\end{aligned}
\tag{18}
$$

where $d(r_1, r_2)$ is the Hamming distance between solution sets r_1 and r_2. The greater $d(r_1, r_2)$ is, the further the solution sets (regions) r_1 and r_2 is. $\delta(r_1, r_2)_{l,m,n}$ is the binary bit used to compare whether $y_{l,m,n}$ is same or not for solution sets r_1 and r_2.

TABLE 1. Multi-Flip Tabu Search Algorithm for Land-Use Planning With BMPs.

Step 1 *Initialization*	Set all the land change variable $y_{l,m,n}$ to zero, run simulation model, and obtain objective function value F^o for base line scenario; set the best objective function value $F^b = F^o$
Step 2 *Random Start Solution*	Randomly choose some fields and flip $y_{l,m,n}$ to 1. Evaluate the objective function value F^s. If F^s is better than the F^o, keep $y_{l,m,n}$ values and set $F^b = F^o$; otherwise, repeat this step until an F^s better than F^o is found
Step 3 *Destruction Phase*	Choose some nonzero $y_{l,m,n}$ that is not on the Tabu list, flip its value back to zero and obtain the objective function value F^d. Repeat this procedure for certain number of iterations, and record F^d that does the least damage to F^b. Set $F^b = F^d$, and use the corresponding $y_{l,m,n}$ to update the Tabu list
Step 4 *Construction Phase*	Choose some $y_{l,m,n}$ that is not on the Tabu list, flip its value to 1 and obtain the objective function value F^c. If F^c is better than F^b, set $F^b = F^c$, and use the corresponding $y_{l,m,n}$ to update the Tabu list. Repeat this procedure for certain number of iterations
Step 5 *Stopping Criteria*	If the stopping criteria are met, terminate the program and report the solution; otherwise, go back to Step 3

By comparing the number of visited regions, it is also possible to measure the coverage of the search space. The higher this number is, the better the algorithm is able to scan different regions of the search space to locate a good solution. The whole procedure repeats in an iterative manner until an optimal or near optimal solution is found.

CASE STUDY FOR GOODWIN CREEK WATERSHED IN MISSISSIPPI

The multi-flip TS algorithm developed in the present study is applied to a hypothetical land-use optimization study in the USDA Goodwin Creek experimental watershed. Located in the bluff hills of the Yazoo River basin in northern Mississippi, the Goodwin Creek watershed has an area of 5,263 acre. It is instrumented for conducting extensive research on upland erosion, stream erosion and sedimentation, and watershed hydrology. Currently, the total area of the watershed is divided into agricultural exploitations (cotton and soybeans), idle pasture, and forest**.** Land use and management practices, including row crops cultivation, influence the rate and total amount of sediment and nutrients delivered to streams (Vieira, 2004).

For this research, Goodwin Creek watershed was first modeled using AnnAGNPS and CCHE1D. Both models were calibrated using field data. TOPAZ is used to define subwatersheds and channel network from elevation data. Sixty-two agricultural fields were chosen as designated land-use change areas, and the remaining pasture and forest areas were left unchanged. For each field, there are four options for land-use change, ranging from corn, cotton, soybeans, and small grains (a total of 4^{62} possible scenarios). The simulation results were stored at four monitoring stations on the river. Figure 3 shows subwatersheds defined by AnnAGNPS, the channel network used by CCHE1D as well as the selected fields and monitoring stations (derived from a LANDSAT7 remote sensing image in 1987).

Historical climate data for 1982 were used for a one-year simulation. Computational results from CCHE1D model at four key locations [i.e., the pollutant outputs including volumetric sediment yield (VSY), total organic nitrogen loadings (TON), and total organic phosphorus loadings (TOP)] were recorded and used for evaluating the environmental score (pollutant index N_i = 3). The following parameters in the model were used: $\omega_{i,k}$ = 0.25, (i = 1, 2, 3, and k = 1, 2, 3, 4), β_1 = 0.4 for VSY, β_2, β_3 = 0.3 for TON and TOP. Table 2 shows a list of cropping and BMPs (including conventional/minimal tillage, fertilizer application, winter weed cover, etc) of four different land-use types. Fertilizer application data based on AnnAGNPS guidelines and database are listed in Table 3 (Vieira, 2004). Net economic benefits of baseline scenario (Equation 4) and scenarios after land-use change (Equation 5) were generated using Table 4, which indicates the operational cost, production quantity, and returns for four land-use types (AgEcon Enterprise Budgets, 2005).

RESULTS AND DISCUSSION

The TS heuristic was programmed using Visual C++ 6.0. The total computational time for the test

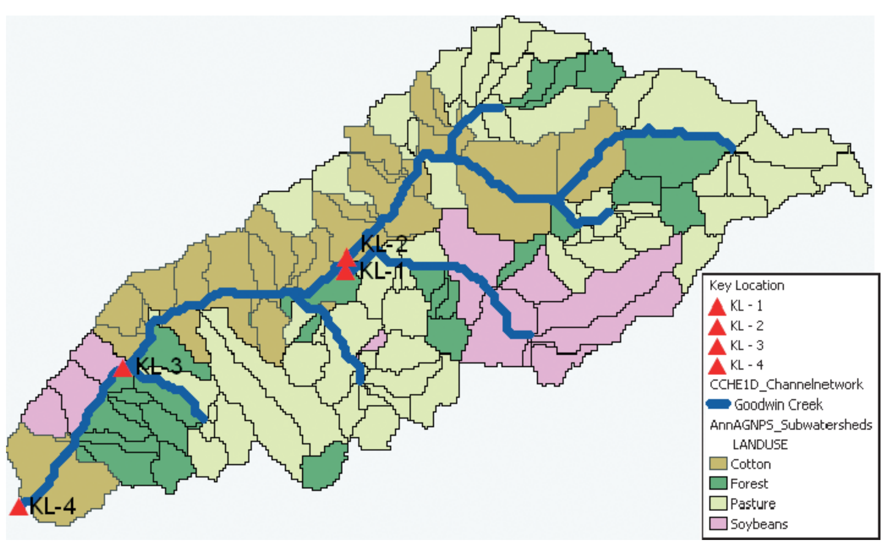

FIGURE 3. Land Uses and Four Key Locations of Goodwin Creek Watershed.

TABLE 2. Crop Management Schedule With Tillage and Fertilizer Application Practices.

Crop	Date	Practice
Corn	03/01	Chisel plow; operation tillage depth 152 mm, sweeps fertilizer (13-13-13), 0 mm depth;
Corn	03/28	Plant, operation tillage depth 51 mm;
Corn	09/01	Harvest crop, residue harvested;
Corn	09/02	Winter bromegrass-weed, begin growth;
Corn	12/31	Growth stops.
Cotton	03/15	Chisel plow; operation tillage depth 132 mm, sweeps fertilizer (13-13-13), 0 mm depth;
Cotton	04/01	Plant, operation tillage depth 31 mm;
Cotton	10/15	Harvest crop, residue harvested;
Cotton	10/16	Winter bromegrass-weed, begin growth;
Cotton	12/31	Growth stops.
Small Grain	06/01	Chisel Plow; operation tillage depth 172 mm, sweeps fertilizer (13-13-13), 0 mm depth;
Small Grain	06/02	Plant, operation tillage depth 71 mm;
Small Grain	10/15	Harvest Crop, residue harvested;
Small Grain	10/16	Winter Bromegrass-weed, begin growth;
Small Grain	12/31	Growth stops.
Soybean	04/01	Chisel Plow; operation tillage depth 152 mm, sweeps fertilizer (Pho-Soy), 25 mm depth;
Soybean	05/01	Plant, operation tillage depth 31 mm;
Soybean	10/15	Harvest Crop, residue harvested;
Soybean	10/16	Winter Bromegrass-weed, begin growth;
Soybean	12/31	Growth stops.

Note: Dates are expressed in MM/DD notation.

TABLE 3. Fertilizer Application Rate for Goodwin Creek Watershed.

Fertilizer Name	Nutrient Description	Mineralizable Nitrogen (%)	Mineralizable Phosphate (%)
13-13-13	Nutricote Total T-180	13	13
Pho-Soy	Diammonium Phosphate	0	74

TABLE 4. Expenses/Returns for Crops per Acre.

Crop Type	Estimated Expenses OC_m ($)	Production Quantity Y_m (bu)	Production Returns B_m ($/bu)
Corn	352.85	175.00	2.34
Cotton	516.30	Lint: 825 (lb)	0.64 ($/lb)
		Seed: 1729 (lb)	0.64 ($/lb)
Small grain	420.32	150.00	3.22
Soybeans	100.41	40.00	5.77

cases considered is around 18.15 hours for 300 iterations on an AMD-Athlon XP 2000+ computer with 512 MB memory. Two separate test cases were conducted; one is land-use optimization with no target area requirement, while the other one is with the target area constraint (Equation 8). It was observed that for both test cases, the search process rapidly converges to near optimal solutions as iteration continues.

Figure 4 shows individual pollutant scores for VSY, TON, TOP, the combined environmental score, economic score, and the total objective function values for the watershed as a function of the iteration number of the TS procedure. It is important to note that for a given iteration, the plotted values are those corresponding to the combination which yielded the best (in this case highest) value of total objective function obtained so far. An exception to this rule occurs when a deconstruction takes place. In this case, the selected previous solution is used for plotting (see iteration number 50). As it can be seen, individual pollutant scores for VSY, TON, and TOP, and the combined environmental score decrease as TS progresses towards the final optimal land-use plan. At the same time, the economic score increases, as more cost-effective land-use scenarios are introduced in the watershed.

Figure 4 also shows the tradeoff needed between environmental and economic scores to reach a Pareto optimal. For example, between iteration numbers 110 and 150, the economic score reaches a plateau and cannot improve anymore. On iteration 150, the search algorithm makes a compromise and accepts a slightly higher (worse) environmental score that does not violate the constraints. This, however, increases the economical score. By looking at these diagrams, the decision makers and stakeholders can decide whether the proposed tradeoffs are acceptable or not.

Table 5 shows the detailed pollutant reduction and net economic return achieved by optimizing land-use plans for the first test case. As can be seen from this table, VSY, TON, and TOP from the watershed reduced by 26.1, 33.9, and 33.3% respectively, whereas the net return increased by 12.6% with respect to the original land-use plans. Although the increase in the economic benefits for this particular case study are relatively small, it is thought that more significant benefit increases can be obtained when more realistic land-use plans with cost-effective BMP options are introduced in the problem.

The final land-use allocation is indicated in Table 6 for the first test case. The solution found by TS algorithm favors soybean among the four designated agricultural land uses with regards to the original land-use plan. A total of 27 fields out of 62 fields, covering about 526.14 ha (56.1% of the total agricultural land-use areas), are assigned for soybean production as compared with 13 fields in the original land-use plan covering 306 ha. The original cotton planting surface is significantly reduced from 632 to 127.46 ha, and now only occupies 13.6% of total agricultural land-use area.

Figure 5 shows the final optimal land-use plan after optimization for the first test case. When compared with Figure 3, it is seen that only six fields

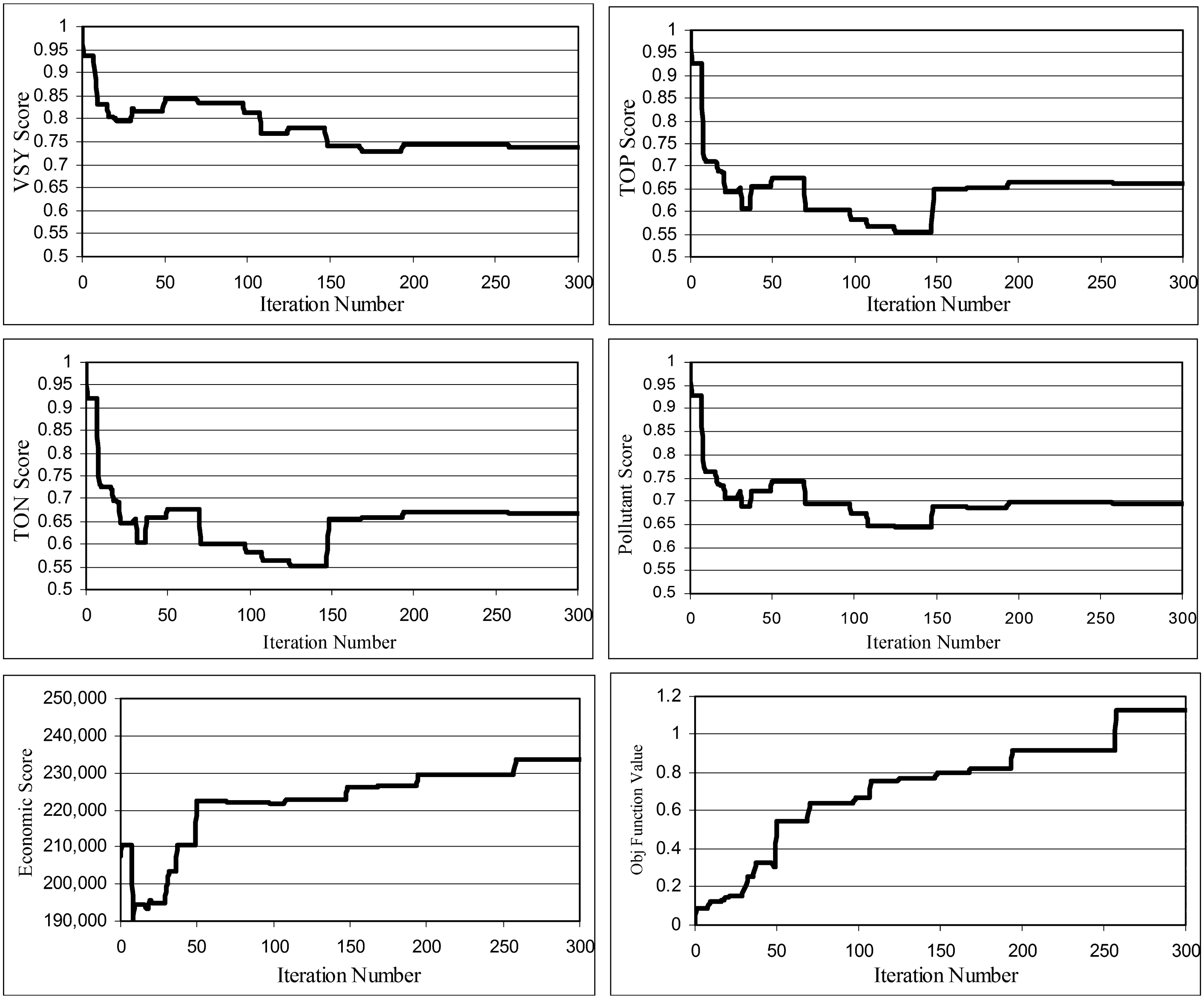

FIGURE 4. VSY, TON, TOP, Pollutant Scores Decrease, While Economic Score, and Overall Objective Function Value Increase as Tabu Search Iteration Continues.

TABLE 5. Optimized Pollutant Reduction Rate, Cost and Economic Return With Flexible Land Use Options.

Pollutant Score and Economic Return	Watershed in Its Original Condition	After Optimization	Percent Change
Volumetric sediment yield	100%	73.9%	−26.1
Total organic phosphors	100%	66.1%	−33.9
Total organic nitrogen	100%	66.7%	−33.3
Economic return ($)	207,372	233,444	+12.6

TABLE 6. Total Area for Agricultural Land Use Before and After Land-Use Changes.

Type	Area (ha, before)	Area (ha, after)
Corn	0	141.03
Cotton	632	127.46
Small grain	0	143.37
Soybeans	306	526.14

remain unchanged. Another interesting observation is that some new land uses, like corn and small grains, have also been introduced. This new land-use plan will not only helps reduce the water quality degradation, but also brings around 233,444 dollars of economic benefits for the watershed, which is a 12.6% increase with respected to the original situation (Table 5). By comparing the final land-use plan in Figure 5 with the original land-use plan in Figure 3,

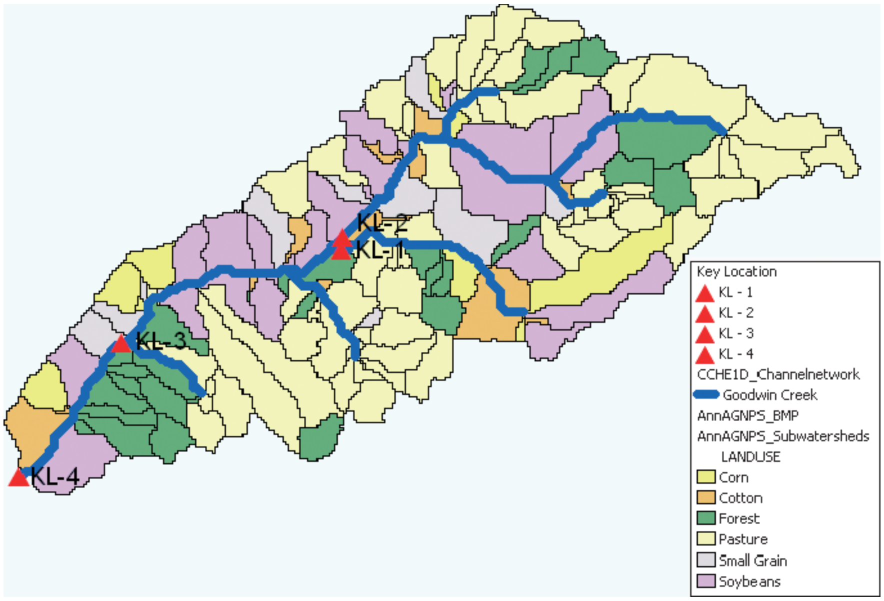

FIGURE 5. Optimal Land-Use Plans After Optimization for Goodwin Creek Watershed.

the decision maker can also identify the fields that play the most important role in overall cost-effectives of the watershed, and that can be used for future agricultural land-use planning and decision making purposes.

The second test case involves a policy constraint (Equation 8), which defines upper limits for the four designated agricultural land-use types. The imposed limits are listed in the second column of Table 7 in terms of both percentage and surface area. The optimization algorithm now tries to find an optimal land-use plan that not only improves objective function value, but also tries to satisfy the upper limits for the surface areas of different land-use types as much as possible. The third column of Table 7 shows the final optimal area allocations after optimization. The TS algorithm still favors the soybean production; 21 fields out of 62 fields choose soybeans, occupying 367.9 ha (39.2% of the total agricultural land-use areas). But as compared with the first test case, this increase has been significantly reduced due to the constraint defining a target surface area for the soybean production. The optimization procedure resulted in a final solution that assigns the soybean production to an area greater than the upper bound. The exceeding amount, however, has been kept to minimum due to penalization of the objective function.

Table 8 shows the detailed pollutant reduction and net economic return achieved by optimizing land-use plans for the second test case. The individual pollutant score like VSY, TON, and TOP, and the combined pollutant score all decreased as iteration continues. Due to the existence of the target area constraints, the net return only increased by 3.6% with respect to the original land-use plans, which is 9% less than the first test case. This is because the land resources are restricted to the upper limits of the land area.

As agricultural researchers, it is obvious that the optimization algorithm favor soybean to some extent in both case studies because soybean minimizes the environmental score compared with the other three crops. Firstly, soybean does not need nitrogen from

TABLE 7. Effect of Upper Limit Area Constraints on Final Optimal Land-Use Plans.

Type	Upper Limit % (area, ha)	After Optimization % (area, ha)	Percent Violations
Corn	20 (188)	19.3 (181)	0
Cotton	30 (281)	27.2 (255)	0
Small grain	20 (188)	14.3 (134)	0
Soybeans	30 (281)	39.2 (368)	+9.2

TABLE 8. Optimized Pollutant Reduction Rate, Economic Return With Constraints of Target Land-Use Area.

Pollutant Score and Economic Return	Watershed in Its Original Condition	After Optimization	Percent Change
Volumetric sediment yield	100%	79.4%	−20.6
Total organic phosphors	100%	63.9%	−36.1
Total organic nitrogen	100%	64.1%	−35.9
Economic return ($)	207,372	214,853	+3.6

fertilization because it is able to fix nitrogen from atmosphere. And secondly, the phosphors fertilizer for soybean was injected into the soil, whereas phosphors were surface-broadcasted for the other three crops, as indicated in Table 2. Different from nitrogen, phosphors is strongly bonded with soil particles. Hence, phosphors applied in soybean land have much lower potential for runoff than other crops with applied phosphors on the soil surface. In a word, fertilization practice determines that soybean has the lowest environmental score.

The results from the two test cases clearly demonstrate that the conceptual modeling framework and the solution methodology described in the present research perform quite well. Using this approach, land-use plans can be optimized to achieve simultaneously the goals regarding the NPS control and economical development. Although the economic module had to be kept simple due to limited available data, the conceptual framework and the solution method served as a useful participatory multi-criteria decision making tool for optimizing agricultural land-use planning at the watershed scale. Due to modular structure of the decision making tool, however, if needed, more advanced and sophisticated economical modules can easily be introduced into the solution procedure.

CONCLUSIONS

Water quality degradation caused by sedimentation, nitrogen, phosphorus, and pesticides can be partly attributes to agricultural operations. One of the IWM approaches, which effectively link agricultural land-use planning including BMPs with environment protection and economic development is a promising direction for long-term sustainable development of the region. However, studying all possible land management strategies on a field-by-field basis for the entire watershed to arrive an optimal solution is a daunting task. Developing an efficient optimization technique which can be used to select optimal land-use designs from a large pool of feasible ones then becomes necessary.

This study established a new conceptual framework which incorporates an integrated modeling system with an optimization technique for agricultural land-use planning with BMPs placement at watershed level. It demonstrated that the proposed framework can successfully accommodate a set of agricultural land-use planning problems, and provide a participatory decision making platform for multiple stakeholders of various background to formulate their own objectives and constraints. The results of the case study of Goodwin Creek watershed in Mississippi indicate that the methodology proposed is valid, and can produce optimal land-use plans that not only improve the environmental quality but also prompt the economic development under certain constraints such as policy, social, and land owner's preferences.

A watershed model AnnAGNPS and a channel network model CCHE1D were linked together to simulate the physically based watershed processes and generated pollutant loads according to a particular land-use configuration. Both models were developed by government agencies and are free to obtain. With user friendly interfaces, both models can be set up with relatively short time depending on the size of watershed to be modeled. An economic model was used to calculate the total watershed cost/benefits given such a land-use configuration. All the models were used in an integrated fashion to provide inputs, including an environmental score and an economic score, for evaluating the objective functions in the optimization module. A set of binary land-use change variables were defined, and their values indicate when some fields were selected to make land changes. During the optimization phase, these variables were flipped using TS heuristics, which take advantage of both short term and long term memories. TS algorithm was found to have great potential for use in land-use optimization problems. Not only did it produce optimal solutions within reasonable timeframe, but also did overcome many difficulties such as definition, starting solutions, and convergence when GA was applied for the same type of problem.

In both case studies, the modeling results show that a given change in land use over the study watershed provides certain increase in profit. It would not be difficult to know how this can translate to an individual land owner. The stakeholders just need to open the final optimal land-use plan, and find the land units that land-use changes have occurred. By comparing the economic profits before and after the land change, the stakeholder can have a clear picture of how the total economic benefits could be translated to each individual land owner. Thus, the stakeholders and the land owners can work together to achieve the sustainable development of the region.

Techniques presented in this study provided an efficient way for the agricultural land-use planning problems. However, the uncertainties arising from the parameterization and model processes are not taken into account because of limited data and information. Future possibilities for extending this research would be to incorporate uncertainties into decision making process, and to analyze the sensitivity and risk associated with various parameters of simulation models and TS by using Fuzzy Logic approach. Thus, stake holders from different levels could discover the data that are available and assemble these data for study of integrated agricultural land-use planning.

ACKNOWLEDGMENT

This work is a result of research sponsored by the USDA Agriculture Research Service under Specific Research Agreement No. 58-6408-2-0062 (monitored by the USDA-ARS National Sedimentation Laboratory) and The University of Mississippi. The authors wish to acknowledge the help of Dr. Ronald Binger and Dr. Yongping Yuan for their help with AnnAGNPS model and data of Goodwin Creek Watershed in Mississippi.

LITERATURE CITED

AgEcon Enterprise Budgets, 2005. AgEcon Enterprise Budgets Including Budgets of Corn, Rice, Soybeans, Cottons, Vegetables, etc.. Department of Agricultural Economics, Mississippi State University, Starkville, Mississippi. http://www.agecon.msstate.edu/Research/budgets.php?t=2005, *accessed* May 5, 2008.

Ballweber, Jeffery A., 1995. Prospects for Comprehensive, Integrated Watershed Management under Existing Law. Water Resource Update 100:19-27.

Bulkley, Jonathan W., 1995. Integrated Watershed Management: Past, Present, and Future. Water Resource Update 100:7-18.

Cerucci, Marcelo, and Jon M. Conrad, 2003. The Use of Binary Optimization and Hydrologic Models to Form Riparian Buffers. Journal of American Water Resources Association 39(5):1167-1180.

Cronshey, R.G., and F.G. Theurer 1998, AnnAGNPS Non-Point Pollutant Loading Model. Proceedings of the First Federal Interagency-Hydrologic Modeling Conference, Las Vegas, Nevada, pp. 1.9-1.16.

Fulcher, Christopher L., 1996. A Watershed Management Decision Support System (WAMADSS): Economic and Environmental Impacts of Land Use Activities for Reducing Nonpoint Source Pollution. PhD dissertation, University of Missouri – Columbia, Columbia, Missouri.

Gilliam, J.W., 1994. Riparian Wetlands and Water Quality. Journal of Environmental Quality 23:896-900.

Gitau, Margaret Watau, 2003. A Quantitative Assessment of BMP Effectiveness for Phosphorus Pollution Control: The Town Brook Watershed, NY. PhD dissertation, The Pennsylvania State University, College Park, Pennsylvania.

Glover, Fred, and Manuel Laguna, 1997. Tabu Search. Kluwer Academic Publishers, Dordrecht, the Netherlands.

Glover, Fred, Eric Taillard, and Dominique de Werra, 1993. A User's Guide to Tabu Search. Annals of Operations Research 41(1-4):3-8.

Harrell, Laura J., and Ranjithan S. Ranji, 2003. Detention Pond Design and Land Use Planning for Watershed Management. Journal of Water Resources Planning and Management 129(2):98-106.

Hilton, Amy, B. Chan, and Teresa B. Culver, 2000. Constraint Handling For Genetic Algorithms In Optimal Remediation Design. Journal of Water Resources Planning and Management 126(3):128-137.

Lin, C.Y., W.C. Chou, and W.T. Lin, 2002. Modeling the Width and Placement of Riparian Vegetated Buffer Strips: a Case Study on the Chi-Jia-Wang Stream, Taiwan. Journal of Environmental Management 66:269-280.

Qi, Honghai, Mustafa Altinakar, Dalmo A. Vieira, and Bahram Alidaee, 2005. Optimized Land Use Planning for Integrated Management of Goodwin Creek Watershed in Mississippi. Proceedings of American Water Resources Association (AWRA) Annual Conference, Seattle, Washington, Nov 2005.

Srivastava, P., J.M. Hamlett, P.D. Robillard, and R.L. Day, 2002. Watershed Optimization of Best Management Practices Using AnnAGNPS and a Genetic Algorithm. Water Resources Research 38(3):3.1-3.14.

Swisher, J.R., P.D. Hyden, S.H. Jacobson, and L.W. Schruben, 2000. A Survey of Simulation Optimization Techniques and Procedures. Winter Simulation Conference Proceedings, Piscataway, New Jersey, Vol. 1, No. 1, pp. 119-128.

Vandeginste, B.G.M., D.L. Massart, L.M.C. Buydens, S. de Jong, P.J. Lewi, and J. Smeyers-Verbeke, 1998. Handbook of Chemometrics and Qualimetrics: Part B. Elsevier, Amsterdam.

Veith, Tamie L., Mary Leigh Wolfe, and Conrad D. Heatwole, 2003. Optimization Procedure for Cost Effective BMP Placement at the Watershed Scale. Journal of the American Water Resources Association 39(6):1331-1343.

Vieira, D.A.N. 2004. Integrated Modeling of Watershed and Channel Processes. PhD Dissertation, the University of Mississippi, Oxford, Massachusetts.

Wang, X., 2001. Integrating Water-quality Management and Land-Use Planning in a Watershed Context. Journal of Environmental Management 61:25-36.

Wang, Sam S.Y., W. Wu, H.M. Hsia, and C.C. Cheng, 2002. Simulation of Flood and Sediment Routing in Ping-Chang River and Pu-Tze River of Taiwan Using CCHE1D model. Proceedings of the Fifth International Conference on Hydroscience and Engineering, Warsaw, Poland.

Zhen, Jenny Xiaoyue, L. Shaw Yu, and Jen-Yang Lin, 2004. Optimal Location and Sizing of Stormwater Basins at Watershed Scale. Journal of Water Resources Planning and Management 130(4):339-347.